

Chapter 1

Managerial Overview of Conjoint Analysis

A great deal of market research commissioned today is descriptive in nature rather than predictive. Descriptive information is useful to characterize demographics, usage patterns, and attitudes of individuals. Beyond descriptive information, managers need survey research tools that can predict what consumers will buy when faced with the variety of brands available and changing product characteristics. It is precisely due to this focus that conjoint or trade-off analysis has become so popular over the last three decades.

Humans employ a variety of heuristics when evaluating product alternatives and choosing in the marketplace. Many products are made up of a dizzying array of features (e.g., laptops, cell phone calling programs, insurance policies, and manufacturing equipment), whereas some are more straightforward (e.g., yogurt, beverages, and light bulbs) and are mainly differentiated by brand, packaging, and price. How does the manager decide which product characteristics, packaging, and branding to use or what price to charge to maximize profits? And how does the consumer evaluate the offering vis-à-vis other alternatives in the marketplace?

To decide what product to sell, managers may use their own intuition or the recommendations of design engineers, or they may look to competitors for indications of what already works. These strategies are myopic and reactive. In consumer-oriented organizations, potential products are often evaluated through concept (market) tests. Buyers are shown a product concept and asked questions regarding their purchase interest, or new products are actually placed in test markets. These tests can be quite expensive and time consuming, and generally investigate just one or a few variations of a product concept. In some surveys, respondents are asked to rate brands and products or to check which brands and product features they prefer. None of these approaches by itself has been consistently successful and cost-efficient. Conjoint analysis uses the best elements of these techniques in a cost-effective survey research approach.

Back in the early 1970s, marketing academics ([Green and Rao 1971](#)) applied the notion of conjoint measurement, which had been proposed by mathematical

psychologists (Luce and Tukey 1964), to solve these complex problems. The general idea was that humans evaluate the overall desirability of a complex product or service based on a function of the value of its separate (yet conjoined) parts. In the simplest form, one might assume an additive model. Consider a laptop PC purchase. A consumer browsing the Internet might see the following alternative:

Dell
750 GB hard drive
7 hour battery life
11-inch display
\$899

Assuming that this consumer uses some internal, subconscious additive point system to evaluate the overall attractiveness of the offer, the unobserved scores (called part-worths) for the attributes of this product for a given buyer might be

<i>Attribute</i>	<i>Part-worth</i>
Dell	20
750 GB hard drive	50
7 hour battery life	5
11-inch display	15
\$899	30
Total utility	120

The estimated overall utility or desirability of this product alternative is equal to the sum of its parts, or 120 utiles. The trick is to obtain these scores from individuals for the variety of attributes we might include in the product or that our competitors might include. To do this reliably, one first develops a list of attributes and multiple levels or degrees within each:

<i>Brand</i>	<i>Hard Drive</i>	<i>Battery Life</i>	<i>Display</i>	<i>Price</i>
Dell	750 GB	7 hour	11-inch	\$599
Acer	1,000 GB	10 hour	14-inch	\$899
HP	2,000 GB	15 hour	18-inch	\$1,199
Lenovo				

It is easy to see that there are many possible combinations of these attribute levels. In the 1970s, it became popular to print each of many product profiles on separate cards and ask respondents to evaluate them by ranking or rating. Consider the conjoint rating question in exhibit 1.1.

By systematically varying the features of the product and observing how respondents react to the resulting product profiles, one can statistically deduce (typically using linear regression) the scores (part-worths) for the separate features re-

How likely are you to purchase this laptop PC?
 Use a scale from 0 to 100, where 0 = *not at all likely*,
 and 100 = *definitely would purchase*.

HP

1,000 GB hard drive

10 hour battery life

11-inch display

\$1,199

Your likelihood to purchase:

Exhibit 1.1. Conjoint rating question

spondents may have been subconsciously using to evaluate products. In contrast to answering direct questions about individual product features, conjoint survey respondents cannot simply say that all features are important—they must trade off different aspects of the product (as in real life), weighing alternatives that have both highly desirable and less desirable qualities.

Using the attribute list developed earlier, there are $(4 \times 3 \times 3 \times 3 \times 3)$ or 324 possible product profiles that could be considered. But what makes conjoint analysis work so nicely is that an individual respondent does not have to evaluate all possible product profiles. If we are willing to assume a simple additive model (which tends to work well in practice), each respondent needs to evaluate only a fraction of the total combinations. With our example, only about eighteen to twenty-four carefully chosen product concepts (using experimental design principles of independence and balance) would need to be evaluated to lead to a complete set of part-worth scores for each respondent for all sixteen attribute levels. The part-worth scores are useful for determining which levels are preferred, and the relative importance of each attribute. Once we know these scores, we can simply sum them to predict how each respondent would react to any of the 324 possible product profiles.

Although the scores on the attribute levels provide significant value in and of themselves, the real value of conjoint analysis comes from the what-if market simulators that can easily be developed, often within spreadsheets. It follows that if, for each respondent, we can predict the overall desirability for all possible product profile combinations (given the set of attribute levels we measured), we can also predict how each respondent might choose if faced with a choice among two or more competing profiles. For example, we can simulate what percent of the

market would prefer each of four laptop PCs (described using the different brands and performance characteristics we measured) if available for purchase. These predictions across a sample of respondents are referred to as shares of choice or shares of preference.

Holding competitive offerings constant, managers can systematically vary the features of their own product profile (such as pricing or performance attributes) and observe what percent of the market would prefer their product under each condition. With conjoint simulators, managers can estimate demand curves and substitution effects, answering questions like, “From which competitors do we take the most share if we increase the processor speed?” They can assess cannibalization effects: “What happens to our overall share if we come out with another product with lesser performance at a lower price?” In essence, managers have the ability to estimate the results of millions of possible concept/market tests based on data collected in a single survey research project among, typically, 300 to 600 respondents. If additional information is included, such as feature costs, computer search algorithms can find optimal product configurations (holding a set of competitors constant) to maximize share, revenue, or profit.

Since the 1970s, as one might expect, additional improvements and refinements have been made to conjoint analysis. In the 1980s, a computerized version of conjoint analysis called Adaptive Conjoint Analysis (ACA) was developed, which could customize the conjoint interview for each respondent, focusing on the attributes, levels, and trade-offs that were most relevant to each individual (Johnson 1987). As a result, more attributes and levels could be studied effectively. In the 1990s, it became popular to ask respondents to simply choose among product profiles rather than rate each profile individually on a numeric scale. The feeling was that buyers in the real world do not actually score each alternative on a rating scale prior to choosing—they simply choose. With choice-based conjoint (CBC), respondents answer perhaps eight to fifteen choice questions such as the one in exhibit 1.2. Today, CBC retains its popularity and is the most commonly used conjoint analysis approach.

Although each question takes longer to read (because there are multiple alternatives to consider), choice-based conjoint questions seem more realistic than the single-concept approach of the 1970s and can include a *none* choice that can be selected if none of the products would appeal to the survey respondent. Developments in computationally intensive statistical methods (hierarchical Bayes estimation) made it possible to estimate a complete set of part-worth scores on each attribute level for each respondent (Allenby, Arora, and Ginter 1995). The results were typically better than with ratings-based conjoint, and the resulting “what-if” market simulators became more accurate in predicting actual market choices.

If you were in the market to purchase a laptop PC today, and if these were your only alternatives, which would you choose?

Dell 2,000 GB hard drive 15 hour battery life 14-inch display \$1,199 <input type="radio"/>	Acer 1,000 GB hard drive 10 hour battery life 14-inch display \$899 <input type="radio"/>	HP 1,000 GB hard drive 7 hour battery life 11-inch display \$599 <input type="radio"/>	None: If these were my only choices, I'd defer my purchase. <input type="radio"/>
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Exhibit 1.2. Choice-based conjoint question

Today, thousands of conjoint studies are conducted each year over the Internet, via hand-held and mobile technologies, or using person-to-person interviews. Leading organizations are saving a great deal of money on research and development costs, successfully using the results to design new products or line extensions, to reposition existing products, and to make more profitable pricing decisions. (See chapter 14 for examples).